OPEN PIT PRODUCTION SCHEDULING APPLYING META HEURISTIC APPROACH

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENT FOR THE DEGREE OF

Bachelor of Technology

In

Mining Engineering

By

BITANSHU DAS

108MN044

DEPARTMENT OF MINING ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY

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Under the Guidance of

Dr. S. Chatterjee

Assistant Professor

DEPARTMENT OF MINING ENGINEERING

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CERTIFICATE

This is to certify that the thesis entitled **"Open Pit Production Scheduling applying Meta Heuristic approach"** submitted by Sri Bitanshu Das (Roll No. 108MN044) in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Mining Engineering at the National institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in this thesis has not formed the basis for the award of any Degree or Diploma or similar title of any university or institution.

Date:

Dr. S. Chatterjee.

Assistant Professor

Deptt. of Mining Engg

NIT, Rourkela -769008

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Date:

(Bitanshu Das)

Roll No. – 108MN044

Department of Mining Engineering

Rourkela - 769008

CONTENTS

ABSTRACT

Production scheduling of a mine is required for effective and economic operations of a mine. Here we are trying to perform production scheduling of mining of mineral blocks under some specific constraints to maximize the profit. The large number of variables and inequalities involved in the process makes it nearly impossible to solve using classical optimization techniques. The techniques and softwares available take a huge amount of time to produce optimized solutions. In this project Genetic Algorithm, a metaheuristic algorithm, has been considered to perform the optimization. The solution provided may not be optimized but will be very nearly optimized and will take significantly lesser time. It starts from a random solution performing several crossovers, mutations and eliminations to reach the optimized solution. A study was carried out in an open pit iron ore mine. The NPV of the mine was found to be a cumulative of over 551 million $. The average stripping ratio was calculated to be 1.72 over the period of 4 years. The computational time required to solve the problem was 31 mins.

List Of Figures:

CHAPTER 1

INTRODUCTION

OBJECTIVE

1. INTRODUCTION

Mine production scheduling is an optimization process which assigns the extraction sequence of a mining block under certain constraints such that it maximizes the net profit. Traditionally, interpolation techniques such as kriging, from the drillhole sample data , is used to build a block model of the ore body for open pit mine planning and design. This single model is assumed to be a fair representation of reality and is used for mine design and optimisation. The design process consists of 3 main steps: (a) finding the block extraction sequence which produces the best net present value (NPV) whilst satisfying the geotechnical slope constraints, and (b) optimising the mining schedule and cut off grades (COG). The NPV of this “optimal” schedule is considered as a main criterion of the economic viability of the project.

The mine production scheduling problems are difficult to solve with commercial solvers. They are large scale mixed integer programming problem having very large dimensions of search space and imposed constraints equations. Solving such problems using classical search algorithms and optimization methods are very difficult and time taking. However there are approaches using which these types of problems can be solved using approximation. In open pit mine planning and production scheduling, Lerchs-Grossmann algorithm combining with heuristic approach is industry standard, although network flow algorithm are also efficient and are well suited. Traditionally mining schedule can be generated by a three step process. First, by implementing the Lerchs-Grossman (L-G) algorithm1 (Whittle 1999) the ultimate pit is obtained. In the second step, the ultimate pit is sub-divided into a series of nested pits, or pushbacks by a different parameterization algorithm, (Seymour 1995). Lastly, an Mixed Integer Program (MIP), or heuristic algorithm, is applied on the series of small pits to obtain the production scheduling (Ramazan and Dimitrakopoulos 2007). The large mine scheduling problem can also be solved by the aggregation of blocks to reduce the number of integer variables (Boland et al. 2009). Though the algorithm provides an optimal solution, it has two major limitations. First, for scheduling a large size deposit, the aggregation approach is also impossible to solve with presently available commercial solvers. Secondly, changing the economic values of the blocks by aggregation, ultimately changes the entire problem into something far different from the original problem.

Various non-traditional methods such as simulated annealing (Albor and Dimitrakopoulos, 2009), genetic algorithms (Pendharkar and Rodger, 2000), tabu search (Lamghari and Dimitrakopoulos 2010) have been applied for solving large scale MIP problems. Metaheuristic algorithm is the method in which a random solution is iteratively improved to reach towards optimization under specific constraints. Metaheuristics make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions (Goldberg, 1989). Metaheuristics do not guarantee that the solution will be optimized but the obtained solution will be very near to the optimal solution in a significantly less computational time (Glover and Kochenberger, 2003). Although, these algorithms have shown significantly improved results in terms of computational time, however, generating the random solutions which satisfy the slope constraints is a cumbersome process.

Though, the computational time in genetic algorithm is significantly less but the main problem associated is to generate the initial chromosomes satisfying the constraints of the problem. In this thesis, all the constrained equations of the optimization problem have been incorporated in the objective function and then the problem has been solved as an unconstrained problem as producing random initial solutions is easier.

Objective

The objectives of this thesis are the following:

- To create an algorithm that will incorporate the constraints in the objective function and process the data to provide solution in a significantly less time compared to the available techniques.
- To calculate the ultimate pit, net present value (NPV) and stripping ratio of the mine from the generated optimal solution

CHAPTER 2

LITERATURE REVIEW

2. LITERATURE REVIEW

The ideal criteria for production scheduling should be maximization of the net present value (NPV) of the pit, but still after four decades of continuing efforts and research, this goal could not be achieved. The pit outline with the highest value cannot be determined until the block values are known. The block values are not known until the mining sequence is determined; and the mining sequence cannot be determined unless the pit outline is available (Whittle, 1999)

Various approaches for production scheduling optimization have been tried. The efforts vary from simulation studies (Pana, 1965), linear and integer programming studies (Barbaro and Ramani, 1986), to dynamic programming (Mukherjee, 1994). Linear programming (LP) and integer programming (IP) approaches have received greater attention among the different methods adopted as applied to production scheduling. But the computational time for these techniques generally increases as the number of constraints increase. Dynamic programming models also limitations in terms of the total number of state variables. These models were unsuitable for real-life situations because only a limited number of possible states (production rates) can be examined at a time. Fuzzy linear programming (Pendharkar, 1997) approach was used to allow for setting fuzzy priorities in the linear programming model. These fuzzy priorities allow for deviations in quality without compromising on overall customer and company satisfaction. In simulation approaches, the optimality of the solution is not guaranteed along with the high overhead in terms of computational time (Pana 1965) making it unpopular for study for production scheduling. Traditional optimization methods like gradient search and local exchange show poor performance (in terms of computer time) in large-scale. Non linear programming (NLP) considers factors like “economies of scale” and “economies of scope” etc which are ignored by linear programming (LP) which considers unit cost independent of the volume of production (economies of scale) and hence giving NLP advantage over LP. The cost estimates in NLP are nonlinear and dependent of the production volume. The NLP problems have varying optimization algorithms depending in problems as no single optimization algorithm works for all NLP problems. The type of objective function and the constraint should be known for selecting an algorithm for solving an NLP problem, (Hiller and Lieberman, 1995) .

Several nontraditional approaches like simulated annealing (SA) algorithms (Albor and Dimitrakopoulos, 2009), the tabu search (TS) (Lamghari and Dimitrakopoulos 2010), and Genetic Algorithms (GA) (Pendharkar and Rodger, 2000) which are based on random, genetic, and neighborhood have been proposed to solve complex, nonlinear optimization problems. Complex, nonlinear problems with several local optima can be solved efficiently by heuristic approaches. Heuristic approaches or hybrids of heuristic-traditional approaches have been proved better than traditional, gradient-based optimization approaches in solving optimization problems with several local optima

Genetic Algorithms are useful for optimization problems with complex search spaces and when the convexity of the objective function is not necessary. Traditional gradient-based optimization methods simulated annealing and tabu search algorithms rely on how close the solutions are to each other. They may either converge to local optimum or take a long time to converge to global optimum (De Jong., 1998). GA, when compared to SA and TS, will necessarily be a better optimization approach when computational time is short and in case of large NP-hard combinatorial problems and complex engineering problems in the continuous domain (Reeves, 1997). But if longer computational time is permitted then TS and SA may outperform GA. The selection of GA parameters, such as the mutation rate, crossover, and population size and sampling of the initial set of population members affects the performance of a GA in a given search space. Ali et al. (2009) applied genetic algorithm in solving linear equation systems. The Genetic Algorithm (GA), a meta heuristic approach, has great advantage for efficient feature selection which provides close to optimum feature subset with a reasonable amount of time (Hong and Cho, 2006).

CHAPTER 3

METHODOLGY

OBJECTIVE FUNCTION

CONSTRAINTS

GENETIC ALGORITHM

3. METHODOLOGY

When solving a mine production scheduling problem, first of all the objective function is formulated i.e. the problem is expressed in the form of a mathematical equation. Then the constraints of the problem are expressed as mathematical equation. In this thesis, the production scheduling problem was solved by incorporating the constraint equations in the objective function to make it easier to generate the initial random pool of solution. After the introduction of the constraint equations in the objective function and imposing the penalizing constants the modified objective function is obtained.

3.1 Objective Function

In general, production scheduling problem can be defined in the form of the following mathematical equation:

$$\max f(x) = \sum_{t=1}^{T} \sum_{i=1}^{N} C_i/(1+r)^t * x_{i,t} \tag{3.1}$$

where $x_{i,t}$ is the i^{th} block extracted at time t

C_i is the Block Economic Value of the $x_{i,t}$ block

i=1,2,3,….,N is the number of block

t=1,2,3,…,T is the number of year

r is the annual rate of interest

3.2 Constraints

3.2.1. Mining Constraints:

Every mine has an extraction constraint. Because of the mining machinery available, it cannot extract beyond a certain tonnage. The following equation shows that the mine on which the study was carried out cannot extract more than *D* tons of material

$\sum_{i=1}^{N} a_i x_i \leq D$ (3.2)

Where a_i is the tonnage of i^{th} block.

Similarly, if a mine extracts below a certain amount of tonnage of material, the machines are likely to remain idle. This is also an unfavorable condition and hence to avoid it, mine production should be more than *E* tons of material expressed by the following equation

$\sum_{i=1}^{N} d_i x_i \geq E$

(3.3)

Where d_i is the tonnage of i^{th} block

3.2.2. Slope Constraints:

The fig 3.1 shows 9 blocks of ore. To extract the 4^{th} block, the 1^{st} and 2^{nd} block should be extracted. Similarly for the extraction of the 5^{th} block, 1st, 2^{nd} and 3^{rd} block should be extracted. To express this, mathematical equations are:

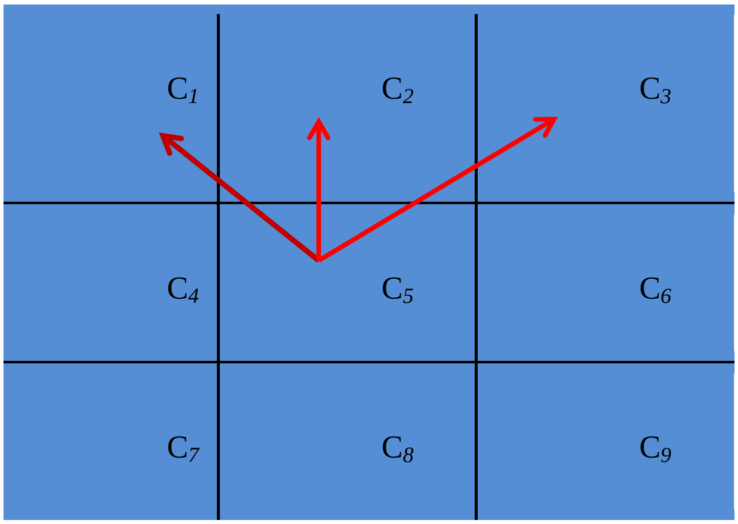


Fig3.1:- Ore body having 9 mineral blocks

- $x_{i,t} - x_{j,t} \leq 0$ (3.4)

3.3.2 Reserve Constraints:

A block is either extracted or it hasn't been extracted. For this, the value 0 is taken for x if the block has been extracted and the value 1 is taken if the block hasn't been extracted.

- $\sum_{i=1}^{N} x_i \leq 1$ (3.5)

Modified Objective Function

In constrained GA, producing random initial set of solutions is a cumbersome task. So, an approach is followed to introduce the constraint equations in the objective functions using penalizing constants to make the problem an unconstrained and hence producing random initial set of solutions is easier.

After introducing the constraint equations in the objective function, the modified objective function is

$$Z = \sum_{t=1}^{T}\sum_{i=1}^{N} C_i/(1+r)^t * x_{i,t} - \mu_1(x_{i,t} - x_{j,t}) - \mu_2(x_{i,t-1} - x_{i,t}) - \mu_3(\sum_{i=1}^{N} a_i x_i - 6.25 * 10^8) - \mu_4(6.20 * 10^8 - d_i x_i)$$

(3.6)

Where, μ_1, μ_2, μ_3 and μ_4 are penalizing constants having very large positive values so that when constraints are violated, the chromosome gets rejected during selection process.

3.4 GENETIC ALGORITHM

The Genetic Algorithm (GA) is a parallel search technique that begins with a set of possible solutions as a population. Each possible solution (population member) is evaluated for its *fitness*. The fitness of a population member is calculated using the objective function. High-fitness population members include solutions that possess either a higher objective function value (in case of maximization) or a lower objective function value (in case of minimization problem); therefore, the fitness of the promising population member is either directly proportional to the objective function value (in case of maximization problems) or inversely proportional to the objective function value (in case of minimization problems). The initial population is created by generating random population members. After evaluating the fitness of each population member, a subsequent generation of population is generated by applying genetic operators, such as selection, crossover, and mutation, to individuals in the current population (Pendharkar and Rodger, 2000). The selection crossover and mutation operators are designed in such a way that, from one generation of population to another, the average fitness of the population generally increases. The best fitness member of any generation is the solution to the optimization problem (De Jong, 1988). GAs mimic some of the processes observed in natural selection through the Darwinian notion of "survival of the fittest".

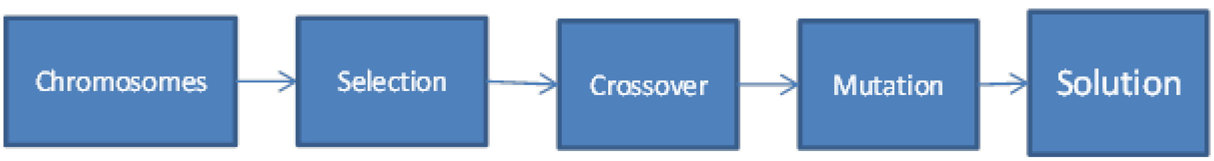


Fig3.2:- Diagram showing different components of GA

Unlike classical techniques, the algorithm works with a population of possible solutions rather than a single solution. The algorithm terminates when either a maximum number of iterations have been performed, or an optimal solution with satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of iterations, a satisfactory solution may or may not have been reached (Goldberg, 1989).

Genetic algorithms are applicable in various fields like bioinformatics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics, etc.

A typical genetic algorithm requires:

- a genetic representation of the solution domain,
- a fitness function to evaluate the solution domain.

The solution is represented as an array of bits. The parts of the bits can be aligned easily because they have a fixed size facilitating simple crossover operations. Due to this property, these genetic representations are convenient. In case of variable length representations, crossover implementation is more complex. In genetic programming, tree-like representations are used whereas the graph-form representations are used in evolutionary programming.

The quality of the represented solution is determined by the fitness function defined, which is always dependent on the problem. In cases where it is hard or even impossible to define the fitness function, interactive genetic algorithm is used.

Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions (usually randomly) and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators (Deb, 2010) as shown in fig 3.2.

3.4.1 Initialization

Initially a random pool of solution is generated to form an initial population. The size of the pool of solution may range from hundreds to thousands or more depending on the nature of the problem. To allow an entire range of possible solution (search space), the initial population is generated randomly. But sometimes the solutions maybe "seeded" in areas where there are more chances of the existence of optimal solutions (Deb, 2010).

To demonstrate the various operations in a GA, a ore body with 9 mineral blocks with economic value C_1, $C_{2,\dots\dots,}$ C_9 are considered and presented in Figure 3.3. The ore body is to be extracted in 3 years. Therefore, the total number of bits in the chromosome is (9x3) 27.

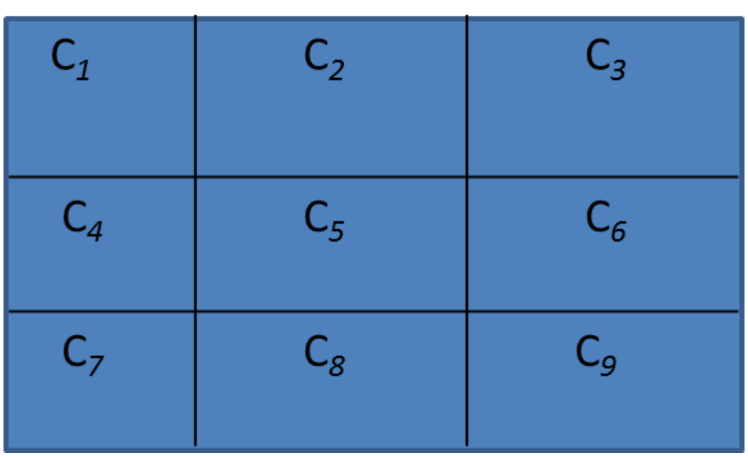


Fig3.3:- Ore body with 9 blocks

Sample Chromosome

0	0	1	1	0	0	1	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	1	1	0

Fig 3.4:- A sample 27-bit chromosome

Each block has 3 bits of chromosomes i.e. 1 bit for each year. So, the chromosome has total 27 bits as represented in fig. 3.4. This is a single random solution. Let there be 50 numbers of random solutions.

3.4.2 Selection

After initialization, individual genomes are chosen from the pool of solution for breeding (recombination or crossover), this stage is called selection. The Individual solutions are then subjected to fitness function and then selected through a fitness based process where the fitter solutions are more likely to get selected. Some methods select the best solution by rating fitness of each solution whereas some methods select by rating a random sample of solution. The first method can be time consuming in case of large problems (Goldberg, 1989).

The selection has been performed by the Roulette wheel selection method. This method is also known as fitness proportionate solution. The fitness function assigns values to possible solutions which are used to determine the probability of selection of each individual chromosome. If f_i is the fitness value of a chromosome i in the population, its probability of being selected is

$$p_i = \frac{f_i}{\Sigma_{j=1}^{N} f_j}, \qquad (3.7)$$

where, N is the number of individuals in the population.

This is similar to a Roulette wheel. A proportion of the wheel is assigned to each of the possible selections based on their fitness value by normalizing them to 1. Then a random selection is made by rotating the roulette wheel (Deb., 2010) as shown in fig 3.5.

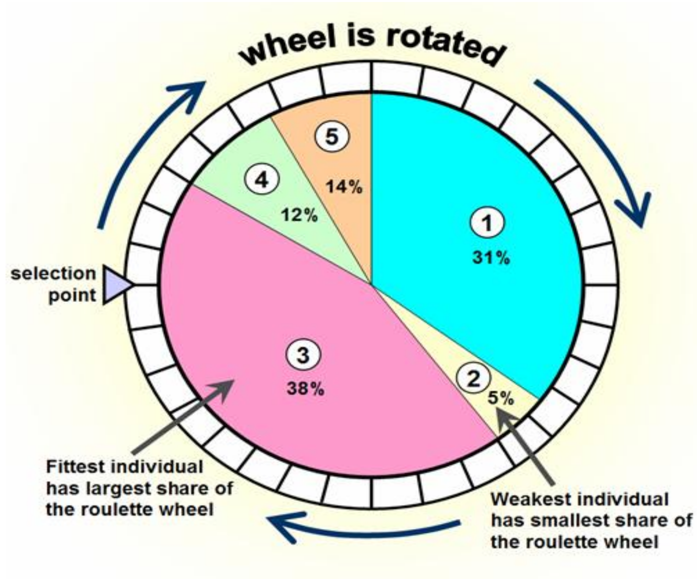


Fig3.5:- Roulette wheel selection

Fig Reference:- http://www.edc.ncl.ac.uk/assets/hilite_graphics/rhjan07g02.png

Sample Chromosome 26

0	0	1	1	0	0	1	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	1	1	0

Sample Chromosome 35

0	0	1	1	0	0	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	0	1	0	1	1	0

Fig 3.6:- Two sample chromosome having highest probability of selection

For an example, say chromosome 26 and 35 (fig 3.6) have the highest share in the roulette wheel and so they have the maximum probability to get selected for reproduction

3.4.3 Reproduction

Once selection is done, the selected solutions are used to generate second generation of population of solutions which is called reproduction. This is achieved through genetic operators: crossover (also called recombination), and/or mutation.

These processes result in producing next generation of population of solutions that is different from the initial generation. Generally the average fitness increases by this procedure for the population, since in reproduction only the selected fitter solutions are considered (Goldberg, 1989).

- **Crossover**

It is a genetic operator used for producing new set of chromosomes from existing set of chromosomes i.e. producing new generation of solution. It is similar to reproduction and biological crossover existing in nature. In crossover two parent chromosomes are taken and exchange of bits takes place between the parents to produce offspring chromosomes (Deb, 2010) as shown in fig 3.7.

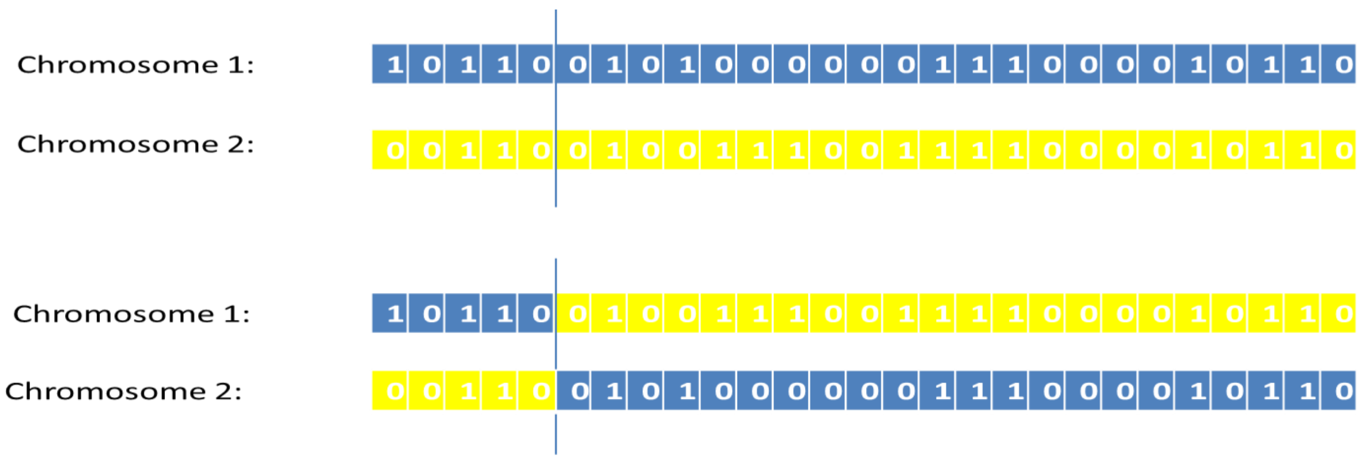


Fig3.7:- Crossover operation in two parent chromosomes from the example problem

- **Mutation**

Mutation operator is used to maintain from one generation of a population of algorithm chromosomes to the next. It is used when a dead end is reached and no further new pool of solutions can be produced. It mutates any random one bit of solution or may be more than one bit of solution to produce new solutions as shown in fig 3.8. Using mutation a better solution is reached but if the probability of mutation is set high then the search will turn into a primitive random search (Deb, 2010).

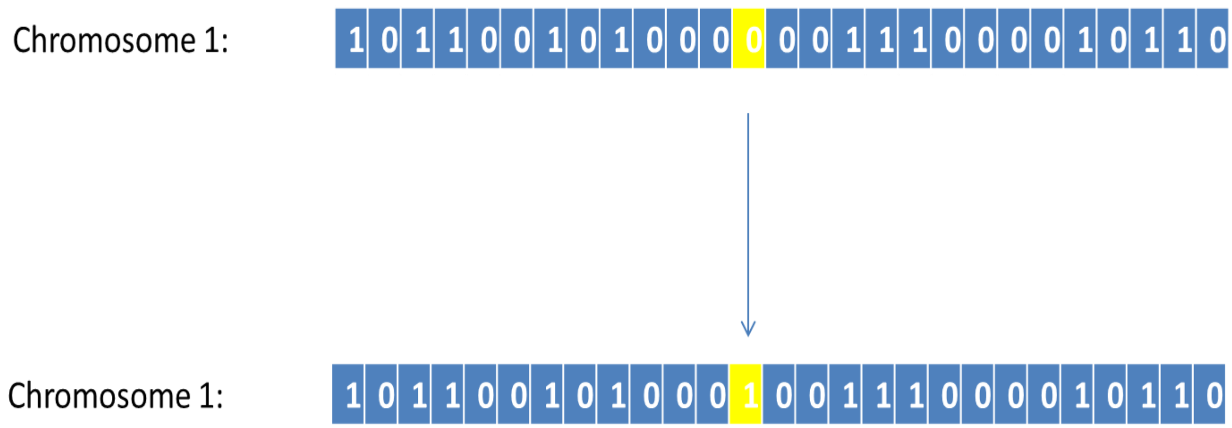


Fig3.8:- Mutation operation to produce new chromosome from parent chromosome

3.4.4 Termination

The ending of the algorithm when a certain condition is reached is called termination (Deb, 2010). The algorithm can be terminated when one or a combination of the following criteria is fulfilled:

- An optimal solution is obtained
- A fixed number of iterations have been performed (50)
- The allocated computational time or money is reached
- The highest ranking has been reached and the algorithm can no longer produce better solution
- Manual inspection

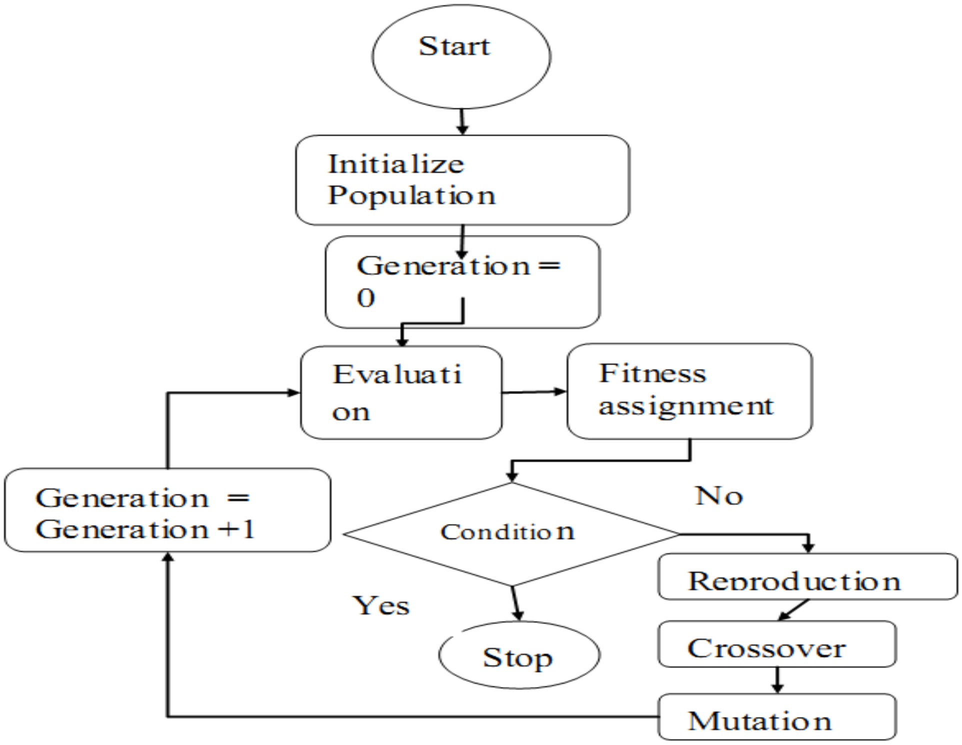


Fig3.9:- Flowchart for working principles of GA

The flowchart in fig 3.9 depicts the whole working principles of GA and steps involved are outlined here:-

1. First of all the population of solution is initialized.
2. The generation counter is set to 0
3. The population is evaluated.
4. It is checked under the fitness function. If the condition is satisfied, the algorithm terminates.
5. If the condition is not fulfilled, the population goes through reproduction, crossover and mutation processes.
6. The generation counter is incremented by 1 and step 3 to 5 is repeated.

CHAPTER 4

CASE STUDY

4. CASE STUDY

The study was carried out on an iron ore mine situated in the south-eastern part of India. The deposit lies between latitude $18^0 41^{'}$ and $18^0 42^{'}$, and longitude $81^0 42^{'}$ and $81^0 12^{'} 30^{''}$. This is a hilly deposit with highly undulating ground level. The highest point of the deposit is 1269 m above the mean sea level (MSL) and the lowest point, upto which mineralization found during the investigation, is at 950 m reduced level. Most of the area of the deposit is covered by green vegetation. The area is drained by seasonal nalahs which are flowing both the sides of the deposit. The geological study of the deposit revealed that this iron ore deposit was formed during the precambrian age. This series of ore consists of iron ore, unenriched banded iron formation rocks (Banded Hematite quartzite), shale, tuff and quartzite. The major iron ore bodies occur along the top of the range and generally at the bottom of the underlying shale. The deposit is situated in the southern ridge of the range. There are numbers of folds, faults present in the mine which indicates that the deposit is highly disturbed in nature. There were 77 borehole data available from the mine for conducting this study. The boreholes are located in a grid pattern; however, the spacing of the boreholes varies from 200-250 meters. The average length of the boreholes is about 100 meters. Samples from the boreholes were collected in cores of less than 1-meter. The mine has seven different lithologies namely Steel Gray Hematite (SGH) Blue hematite (BH), Laminated Hematite (LH), Laterite (L), Blue Dust (BD), Shale (SHL) and Banded Hematite Quartzite (BHQ). Most of the high grade iron ore is associated with still gray, blue and laminated hematite. The average depth of the mine is 160 m. The mine has fourteen working benches with bench height of 12 meter.

CHAPETR 5

RESULTS

ULTIMATE PIT MODEL

NET PRESENT VALUE

STRIPPING RATIO

MINING CONSTRAINT

5. RESULTS

The resource of the deposit was estimated using ordinary kriging method using the 5 m composited borehole data (Chatterjee, 2006). The number of estimated blocks in the deposit is 47275. The size of the estimated block is 50 m x 50 m x 10 m. The production scheduling was performed for 4 years and hence the sample chromosomes had 189100 (47275x4) bits. Now the mining constraints and slope constraints were determined. The mine had a maximum capacity of producing 6.25×10^8 tons of material per year. To prevent the machines from being idle, the mine should produce 6.20×10^8 tons of material per year. The maximum number of iterations was set to 50. The mutation rate for the problem was defined to be 0.1. The amount of time taken to solve this problem is 31 minute.

The fig. 5.1 shows that the mine produced the tonnage of material almost at a constant rate. The value of the mineral produced throughout the life of the mine is always within the range of mining constraints. From the figure, it is observed that the mine has produced 6.23×10^8 tons of material every year i.e. the mining constraint was followed.

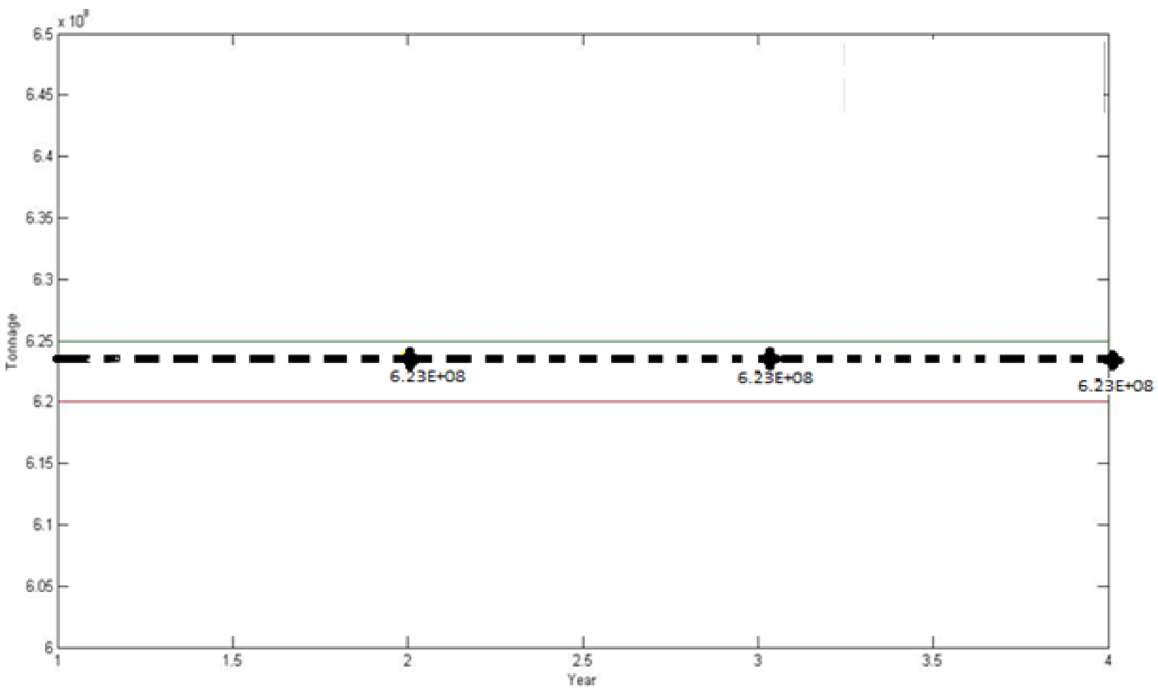
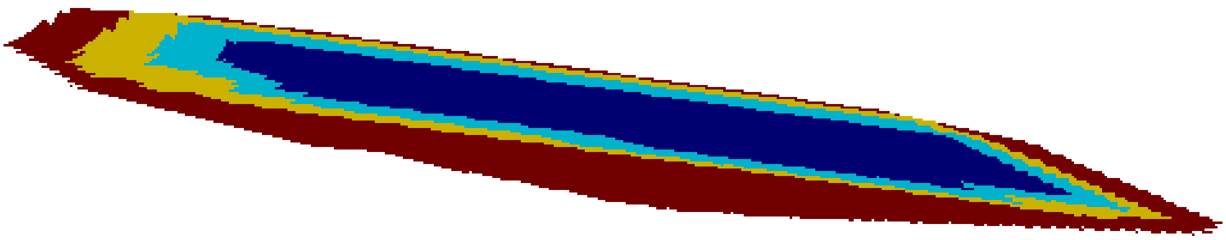


Fig5.1:-Tonnage extracted per year grapgh

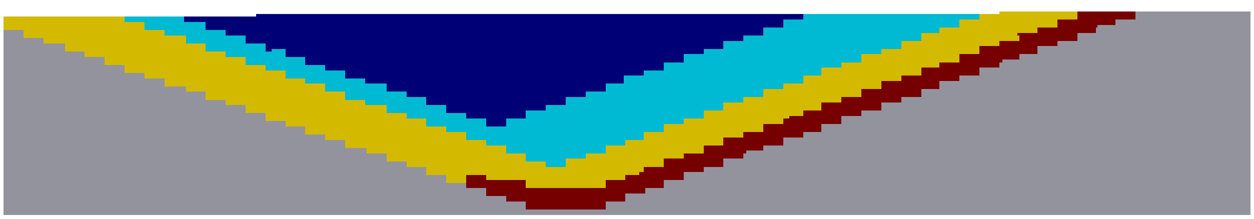
The ultimate pit of a mine is defined to be that contour which is the result of extracting the volume of material which provides the total maximum profit whilst satisfying the operational requirement of safe wall slopes. The ultimate pit limit gives the shape of the mine at the end of its life.



Color Index: 

No. of year: 1 2 3 4

Fig5.2:- 3D view of the ultimate pit



Color Index: 

No. of year: 1 2 3 4

Fig5.3:- Ultimate Pit in Y-Z axis

The ultimate pit model obtained as shown in fig. 5.2 and 5.3 show the section of the mine that are going to be extracted over the period of 4 years. The deep blue color represents the section of the mine that is scheduled to be extracted in the 1st year. The lighter blue color indicates the ore body scheduled to be extracted in the 2nd year. The yellow and brown colored sections shows the ore scheduled to be extracted in the 3rd and 4th year. From the ultimate pit model, it was observed that the slope constraint has been followed and also no ore block has been extracted twice and hence the reserve constraint has been followed

Net Present value (NPV) of a time series of cash flows, both incoming and outgoing, is defined as the sum of the present values (PVs) of the individual discounted cash flows of the same entity.

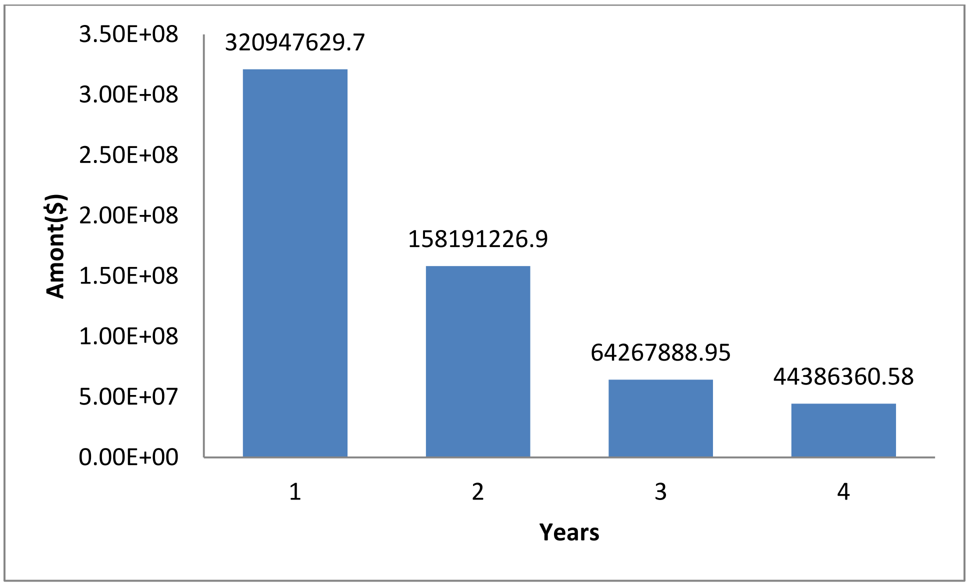


Fig5.4:- The bar graph of DCF for each individual year

The bar graph shown in fig 5.4 demonstrates that the discounted cash flow (DCF) in each individual year. The 1st year has the maximum profit as cash is needed at the startup to keep the venture running for subsequent years. Also the best parts of the mine are extracted in the 1st year and hence the highest profit is obtained in 1st year.

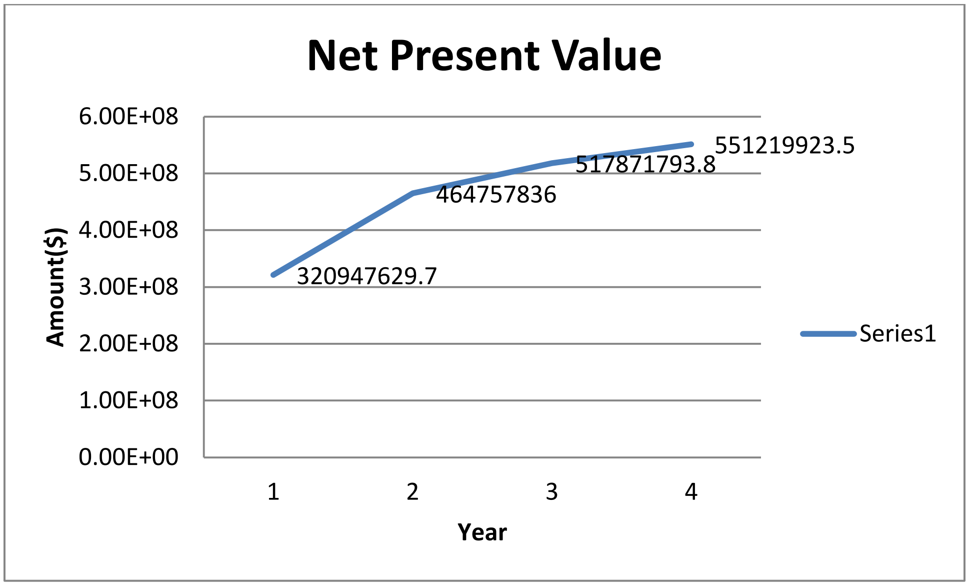


Fig5.5:- The cumulative line graph of NPV for the mine

The cumulative graph in fig 5.5 shows that the NPV of the mine never goes down i.e. it always remain in profit The Net Present Value of the mine for 4 years was calculated to be 551 million $.

Stripping ratio refers to the ratio of the volume of overburden (or waste material) required to be handled in order to extract some volume of ore.

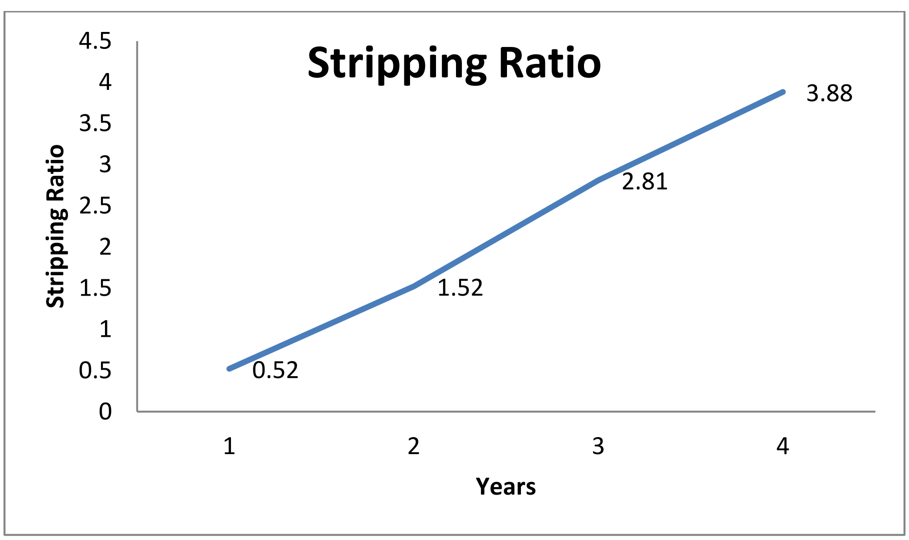


Fig5.6:- The Stripping Ratio for each Year.

The Stripping Ratio in the first year was 0.52 which rises up to 3.88 by the 4^{th} year as shown in fig 5.6. This is because as the time passes, the ore blocks get extracted leaving the waste blocks. Hence for further removal of ore blocks, more overburden removal is required in subsequent years. The average Stripping Ratio over the period of 4 years was found to be 1.72.

CHAPTER 6

CONCLUSION

6. CONCLUSION

A study was carried out to solve an optimization problem of production scheduling of an open pit mine using a meta heuristic approach. The meta heuristic approach selected was Genetic Algorithm. Genetic Algorithms are known to provide solutions to complex problems handling large variables and constraints in significantly less time.

The iron ore mine had 47275 numbers of blocks that needed to be extracted over a period of 4 years i.e. the total number of variables in the search space is 189100. This problem could not have been solved by tradition methods. The computational time required for solving the production scheduling problem of Iron Ore Mine having 47275 blocks for a period of four years after 50 iterations was just 31 minutes for a Pentium i3 2.1 GHz processor which emphasizes that the computational time for solving the problem using GA is significantly less. The results obtained were used to calculate the ultimate pit, net present value and Stripping ratio. No constraint was violated in the algorithm.

Hence incorporating the constraint equations in the objective to and solving the derived unconstrained expression using genetic algorithm can be a viable method of optimization problems of an open pit mine.

The limitation of the present work is that the obtained results have not been compared with any optimum solution. To know the ability of the proposed approach, a valid comparison study is required.

CHAPTER 7

REFERENCES

7. REFERENCES

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